Transformation Based Endorsement Systems

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Abstract: Evidential reasoning techniques classically represent support for a hypothesis by a numeric value or an evidential interval. The combination of support is performed by an arithmetic rule which often requires restrictions to be placed on the set of possibilities. These assumptions usually require the hypotheses to be exhausitive and mutually exclusive. Endorsement based classification systems represent support for the alternatives symbolically rather than numerically. A framework for constructing endorsement systems is presented in which transformations are defined to generate and update the knowledge base. The interaction of the knowledge base and transformations produces a non-monotonic reasoning system. Two endorsement based reasoning systems are presented to demonstrate the flexibility of the transformational approach for reasoning with ambiguous and inconsistent information.

1 Introduction

Classification systems are designed to determine the identity of an object from a set of possibilities. Evidence is acquired and interpreted to provide support for the alternatives. Historically, numeric measures have been used to represent the support for the alternatives. Common numeric systems for combining evidential support include certainty factors [2, Chapters 10-11], Bayesian probability and the Dempster-Shafer theory of evidential reasoning [5]. Endorsement based reasoning was introduced by Cohen [3] and Sullivan and Cohen [6] to provide a framework for the symbolic representation and combination of evidential support.

Numeric representations of support, in which the likelihood of a possibility is often indicated by a single value or by an evidential interval, have distinct computational advantages. The combination of support is accomplished by a straightforward arithmetic calculation such as Bayes' rule or Dempster's rule. Moreover, a ranking of the likelihood of the alternatives can be obtained directly from the associated values.

The disadvantages associated with the numeric representation of support have been well chronicled. Difficulties with the use of probabilistic techniques for evidential reasoning are presented in Tversky and Kahneman [7] and Quinlan [4]. Shafer [5] discusses the inadequacy of a single point measure for representing evidential support. Experiments by Buchanan and Shortliffe [2, Chapter 10] exhibit the lack of sensitivity in system performance to changes in the numeric values. The standard numeric techniques also fail when presented inconsistent information. When this occurs, the result of the computation of both Bayes' rule and Dempster's rule is undefined.

An endorsement based system uses symbolic interpretations of the information, endorsements, to represent and combine evidential support. Rather than translating the evidence into a form suitable for a predefined combination rule, the combination techniques are specifically designed for the evidential information of the particular domain. Ranking the alternatives requires an analysis of the endorsements in the knowledge base. Separating the evaluation of the alternatives from the support combination techniques adds flexibility to the reasoning system. It is this separation that permits endorsement based systems to develop hypotheses from inconsistent information.

2 Ambiguity and Inconsistency

Many classification problems can be formulated as questions of the propagation of support in a hierarchy. The relationships of the hierarchy are defined by set inclusion. The alternatives are distinguished by the presence or absence of certain characteristics. For example, a medical diagnosis system attempts to identify a disease from the information provided by the observed symptoms and test results. The diseases comprise the set of possibilities and the characteristics are the symptoms. For identification purposes, a disease is completely characterized by its symptoms.

Formally, a classification hierarchy is defined by two sets; the characteristics C and possibilities P. A possibility is defined as a subset of characteristics. A simple hierarchy is illustrated in *Figure* 1. Throughout this paper, variables
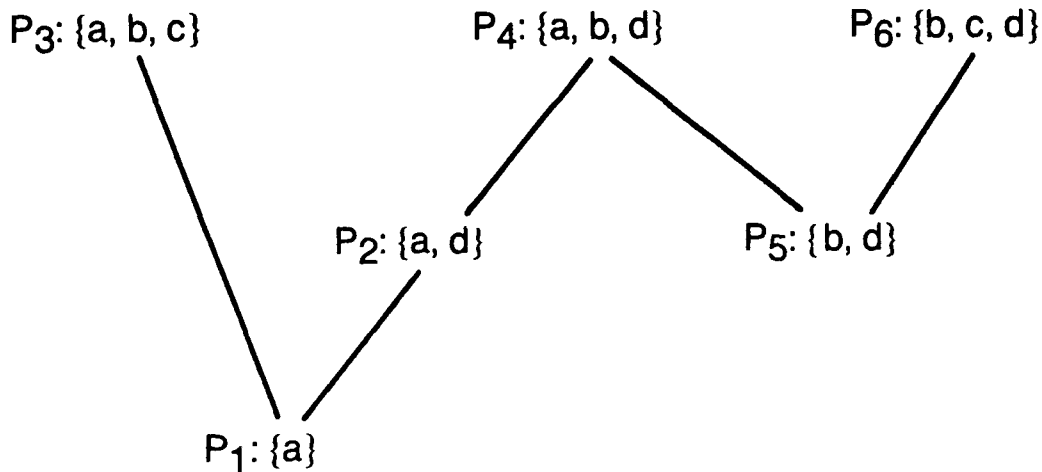
P_3: {a, b, c} P_4: {a, b, d} P_6: {b, c, d}

P_2: {a, d} P_5: {b, d}

P_1: {a}

Figure 1. A characteristic, possibility hierarchy.

x and y are used to denote characteristics while X and Y denote possibilities.

Evidence supporting the presence of characteristic a and the absence of d in the hierarchy defined in *Figure* 1 is *ambiguous* since both P_1 and P_3 are consistent with this information. The addition of evidence supporting the presence of c produces unambiguous evidence; P_3 is the sole consistent possibility. Finally, acquiring information that denies the presence of b provides an example of *hierarchic inconsistency*; there are no possibilities that agree with the accumulated data.

3 A Transformation System

The use of transformation rules to define the combination of support in an endorsement based system is demonstrated by the system GET (Generation of Endorsements by Transformations). The objective is to identify a possibility by acquiring information pertaining to the presence or absence of characteristics. The transformations that define the support combination techniques assert and delete endorsements. The set of asserted endorsements is referred to as the knowledge base. The endorsements for in the system GET are given in Table 1.

Evidence supporting the presence of a characteristic x is denoted $p(x)$, $a(x)$ denotes evidence that indicates the absence of characteristic x. Because of the simplicity of the evidential information, several important capabilities of the transformational approach are not exhibited in this system. Extensions to this basic model are described in Sections 4 and 5.

GET utilizes two types of endorsements; *evidential* and *derived*. Evidential endorsements m, n and d are generated directly from the evidence and the relationships that define the hierarchy. The endorsement $m(x, Y)$ is asserted whenever evidence $p(x)$ is processed and x is a characteristic of Y. The evidential endorsement $n(x, Y)$ is asserted when evidence is obtained that indicates the presence of a characteristic not in Y. Similarly, $d(x, Y)$ is added to the .knowledge base when evidence is obtained indicating the absence of x and x is a characteristic of Y. The endorsement $m(x, Y)$ offers positive support for the possibility Y. The endorsements $n(x, Y)$ and $d(x, Y)$ are negative, they indicate a disagreement between the evidence and the composition of Y.

Derived endorsements are produced by the transformations that define the combination of support. The derived endorsements of GET are s, c, o, and i. These endorsements indicate the consistency of a possibility with the accumulated evidence and are similar to those used by Sullivan and Cohen [6] for recognizing plans.

The knowledge base is maintained by transformations that insert and delete endorsements. The transformations are mainted by two types of rules; *replacement rules* and *generation rules*. Endorsements are generated by rules of the form

$$condition \Rightarrow endorsement$$

where the condition may refer to the evidence and to endorsements in the knowledge base. When the condition is satisfied, the rule adds the endorsement to the knowledge base. The generation rules are applied only when the endorsement on the right-hand side is not currently asserted. Consequently, the knowledge base will not contain duplicate endorsements.

A replacement rule has the form

$$e_1, \ldots, e_n \rightarrow f_1, \ldots, f_k$$

144

endorsement	interpretation
$m(x, Y)$	x, whose presence is supported, is a member of Y
$n(x, Y)$	x, whose presence is supported, is not a member of Y
$d(x, Y)$	x, whose absence is supported, is a member of Y
$s(Y)$	Y is the sole consistent possibility
$c(Y)$	Y is consistent
$o(Y)$	Y is only one of several consistent possibilities (other consistent possibilities)
$i(Y)$	Y is inconsistent

generation rules

1. $p(x)$ & $member(x, Y) \Rightarrow m(x, Y)$
2. $p(x)$ & $\neg member(x, Y) \Rightarrow n(x, Y)$
3. $a(x)$ & $member(x, Y) \Rightarrow d(x, Y)$
4. $n(x, Y) \Rightarrow i(Y)$
5. $d(x, Y) \Rightarrow i(Y)$
6. $c(Y)$ & $\exists(X)(X \neq Y$ & $c(X)) \Rightarrow o(Y)$
7. $c(Y)$ & $\forall(X)(X \neq Y \rightarrow i(X)) \Rightarrow s(Y)$

replacement rules

8. $s(Y), c(Y) \rightarrow s(Y)$
9. $s(Y), o(Y) \rightarrow s(Y)$
10. $i(Y), s(Y) \rightarrow i(Y)$
11. $i(Y), c(Y) \rightarrow i(Y)$
12. $i(Y), o(Y) \rightarrow i(Y)$

Table 1: Endorsements and Transformations for GET

where e_i and f_j are endorsements and the f's comprise a subset of the e's. A replacement rule is triggered when the endorsements comprising the left-hand side are in the knowledge base. The rule replaces the endorsements on the left-hand side with those on the right. The ability of replacement rules to update the knowledge base as information is acquired produces a non-monotonic support system. For example, the simultaneous presence of endorsements $c(X)$ and $i(X)$ causes the deletion of the consistency endorsement. The rules that define the propagation of support in GET are given in Table 1. The predicate $member(x, Y)$ is satisfied whenever x is a characteristic of Y.

A dominance relation on the derived endorsements is defined by rules 8–12. When a possibility X has been assigned endorsements specifying that it is both consistent and the sole consistent possibility, the former endorsement is removed since it is less informative than the endorsement $s(Y)$. Similarly, the presence of an inconsistency removes all endorsements designating consistency.

Initially, every possibility is assigned the consistency endorsement c. For a system to be consistent, it must agree with all of the acquired evidence. Two types of inconsistency can occur in a hierarchic reasoning system: *evidential* and *hierarchic*. Evidential inconsistency occurs when evidence is acquired that generates both $p(x)$ and $a(x)$. Hierarchic inconsistency results from the acquistion evidentially consistent information that is incompatible with each of the possibilities in the hierarchy.

Even when no possibility agrees with the totality of the evidence, the endorsements still contain information that may be used in determining a likely candidate. Evaluating the likelihood of the alternatives requires the addition of a component that examines the composition of the knowledge base. In GET, the alternatives are ranked using the number of positive endorsements, negative endorsements and the number of characteristics that define the possibility.

For a possibility Y, let $pos(Y)$ denote the number of positive endorsements for Y. That is, the number of endorsements of the form $m(x, Y)$. Similarly, $neg(Y)$ denotes the number of negative endorsements. The support for a possibility is defined to be

$$sup(Y) = (pos(Y) - neg(Y))/card(Y)$$

where $card(Y)$ is the cardinality of Y. A possibility X is deemed more likely than Y whenever X is consistent and Y is inconsistent or X and Y have the same consistency endorsement and $sup(X) > sup(Y)$.

The use of $card(Y)$ in computing $sup(Y)$ measures the lack of information concerning the characteristics of Y. *Figure* 2 traces the processing of information concerning the hierarchy in *Figure* 1. The possibilities are listed in the order specified by the ranking defined above. When evidence $p(a)$ and $a(d)$ is processed, $sup(P_1) = 1$ and $sup(P_3) = \frac{1}{3}$ even though both have one positive endorsement. P_3 is supported to a lesser degree since it contains elements for which no evidence has been acquired.

The final combination of evidence produces hierarchic inconsistency. The analysis designates P_3 as the most likely candidate since it has the most positive and fewest negative endorsements.

4 An identification system

Many identification problems acquire and evaluate information gathered from disparate sources. With this in mind, Borigda and Imielinski [1] proposed the process of decision making in a committee as a general framework for the analysis of uncertainty. In a committee deliberation, certain opinions carry more weight than others. This may be due to the level of expertise or the status (i.e. the chairman) of the committee member. An endorsement system can use multiple endorsements to determine a consensus of opinion. The strength of an endorsement may be reflected in combination rules and in the evaluation strategy.

A transformation based endorsement system was constructed to determine the identity of a person from descriptions of the physical characteristics of the person. Information for a database containing height, weight, sex and hair color was obtained, sometimes grudgingly, from the faculty and graduate students of the Wright State University computer science department. Evidence provided to the system consists of the quality of the observation and an estimate of a physical characteristic. An observation is either excellent and impaired; an impaired observation may be one made under less than ideal circumstances or by an inexperienced observer.

An observation generates endorsements for each person in the database. The endorsements indicate the proximity of the estimate to the recorded value. The endorsements are match (ma), possible match (po), unlikely (un) and improbable (im). The appropriate endorsement is determined by a range specified for each physical characteristic. For example, the weight endorsement is determined by the difference of the estimated weight (wte) and the weight recorded in the database (wtp) as follows:

ma	if $|wte - wtp| \leq 5$
po	if $5 < |wte - wtp| \leq 10$
un	if $10 < |wte - wtp| \leq 15$
im	if $|wte - wtp| > 15$

The endorsements for height are determined in a similar manner. A menu containing a spectrum of colors is given for the hair color estimate. A match endorsement is generated when the estimate is identical to the hair color in a database entry. The possible endorsement is generated if the estimate differs by only one position in the spectrum. For example, the possible endorsement is assigned to every person in the database whose hair color is brown or blond when light brown hair is specified by the observer. Match and improbable are the only endorsements assigned for the sex characteristic.

An endorsement has four arguments; the name of the person to whom the endorsement refers, the physical characteristic, a time tag and the quality of observation. The time tag is an integer that records the number of the observation that produced the endorsement. The endorsement

$$po(johnsmith, weight, 5, ex)$$

is generated when the database entry for John Smith's weight is 190 pounds and the fifth observation estimates the weight of the unknown individual as 183 pounds. Another observation that estimates the weight at 181 pounds produces an endorsement that differs from the preceding endorsement only in the time tag.

The cycle of evidence acquisition and endorsement generation follows the pattern presented in the previous section. The analysis of the endorsements establishes a measure of agreement between the observed physical characteristics and each person in the database. For each person p and characteristic c, the value $0 < agree(p, c) < 10$ is determined by the number and quality of the endorsements referring to that characteristic. Endorsements are assigned weights as follows:

	excellent	impaired
ma	10	6
po	7	2
im	3	0
un	0	0

To rank of the alternatives, we let $ex(p, c)$ and $im(p, c)$ denote the mean of the weights of the excellent and impaired endorsements for a person p and characteristic c, respectively. When there are no excellent observations, the evaluation uses the only information available. The acquisition of excellent observations reduces the dependence of the identification on less reliable information. This is reflected by degrading the significance of impaired observations.

excellent observations	$agree(p, c)$
0	$im(p, c)$
1	$\frac{7}{10}ex(p, c) + \frac{1}{2}im(p, c)$
2	$\frac{8}{10}ex(p, c) + \frac{1}{3}im(p, c)$
3	$\frac{9}{10}ex(p, c) + \frac{1}{6}im(p, c)$
4 or more	$ex(p, c)$

When there are four or more excellent observations, the impaired observations are no longer used. To obtain the highest possible rating, there must be at least two observations, one of which is excellent. Moreover, all of the observations must generate the ma endorsement. An individual's ranking is the sum of the values of the associated with the four characteristics.

The analysis of the alternatives in the identification system illustrates one of the fundamental properties of endorsement based reasoning. The value of an endorsement is dynamic, it may change as additional information is obtained and added to the knowledge base. The evaluation uses the information recorded in the endorsements to determine the weight of the evidence. This is what Sulli-

van and Cohen [6] refer to as explicitly reasoning with the causes of uncertainty rather than implicitly manipulating uncertainty through a numerical calculus. The endorsement system permits the re-evaluation of the significance of evidence based on the totality of all evidence that has been processed.

5 Conclusions

The systems described in this paper demonstrate a transformation based approach to the representation and combination of evidential support. Rules for the combination and propagation support are designed for the particular problem domain. The specification of knowledge base transformations as generation and replacement rules permits a straightforward translation of the system design into a Prolog implementation.

Advantages of endorsement based systems include the expressibility of the evidential representation and the flexibility of support propagation and evaluation techniques. Increasing the information in an endorsement provides additional capabilities to a symbolic reasoning system. Predicates can be added to replacement rules to produce time dependent analysis. The comparison of tags in endorsements **e** and **f**

$$\mathbf{e}(i,Y), \mathbf{f}(j,Y), i > j \to \mathbf{e}(i,Y)$$

$$\mathbf{e}(i,Y), \mathbf{f}(j,Y), j > i \to \mathbf{f}(i,Y)$$

defines a *recency* precedence of endorsements. In a time dependent problem domain, the dynamic capabilities of endorsement analysis can be used to give additional creedence to recently obtained information.

In a symbolic reasoning system, the evidence and combining rules can be direct translations of domain information and reasoning. The endorsements in the knowlege represent the accumulated information. Unlike the numeric systems in which the alternatives are ranked by the associated values, assigning a measure of likelhood to the possibilities in an endorsement system is obtained by analyzing the contents of the knowledge base. Advances in endorsement based reasoning requires developing efficient techniques for evaluating the knowledge base.

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